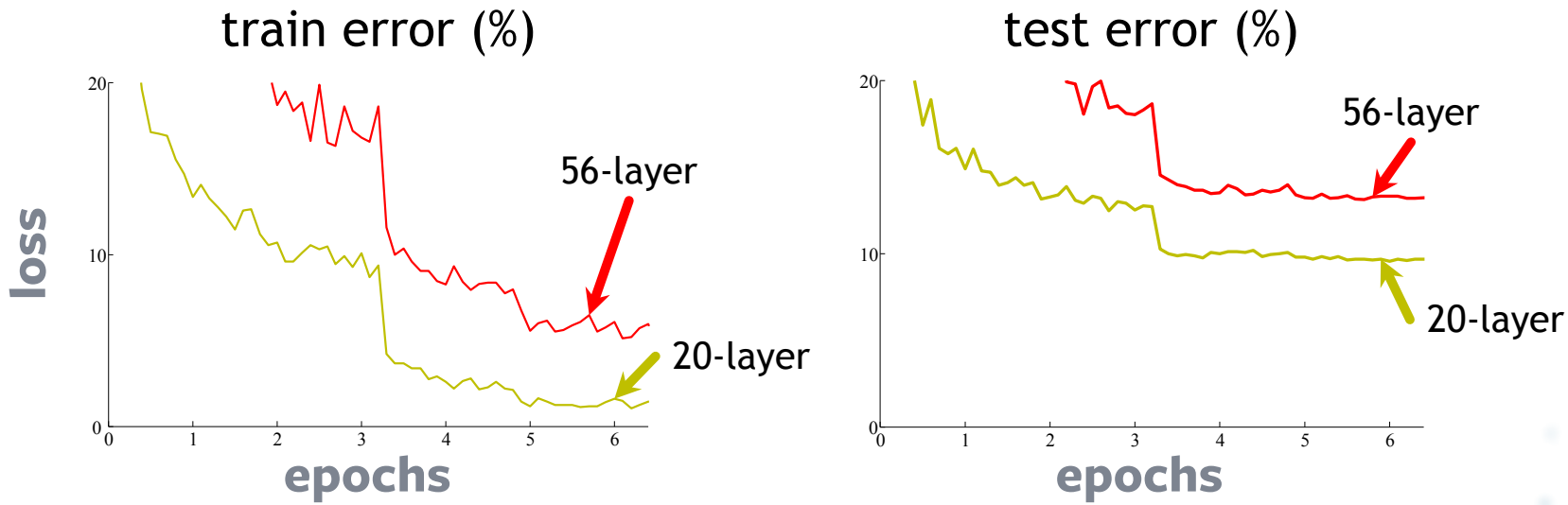
Advanced Topics in Machine Learning: Convolutional Networks (Part 3)

Laurens van der Maaten and Aaron Adcock


I WAS WINNING IMAGENET
UNTIL A DEEPER MODEL CAME ALONG
imgflip.com

Stacking layers

- Simple experiment with stacking many 3x3 convolutional blocks:



* Figure credit: Kaiming He

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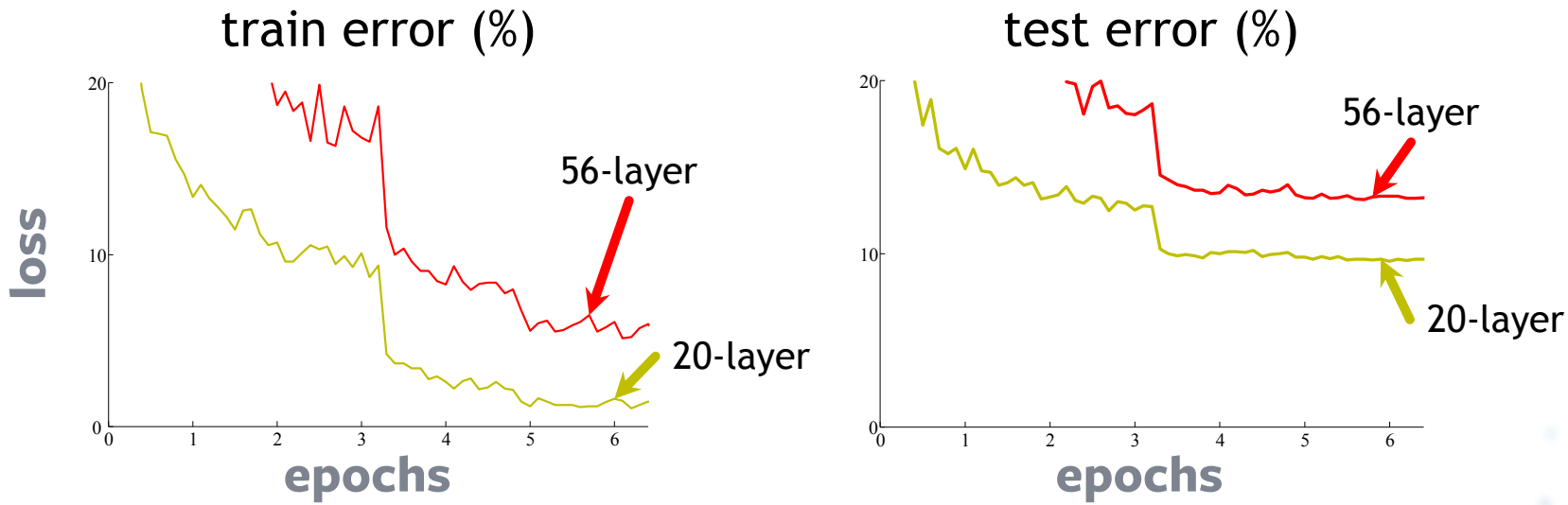

- Does this suggest overfitting?

* Figure credit: Kaiming He

Stacking layers

- Deeper models should not have higher training error

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Stacking layers

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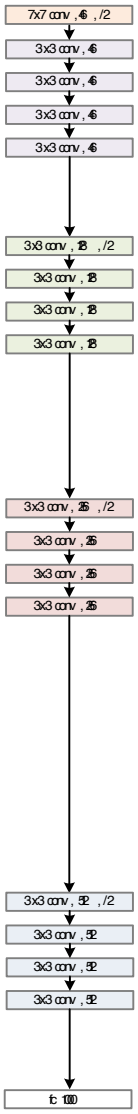
- Solution by construction:
  - Train shallow model

"shallow" model



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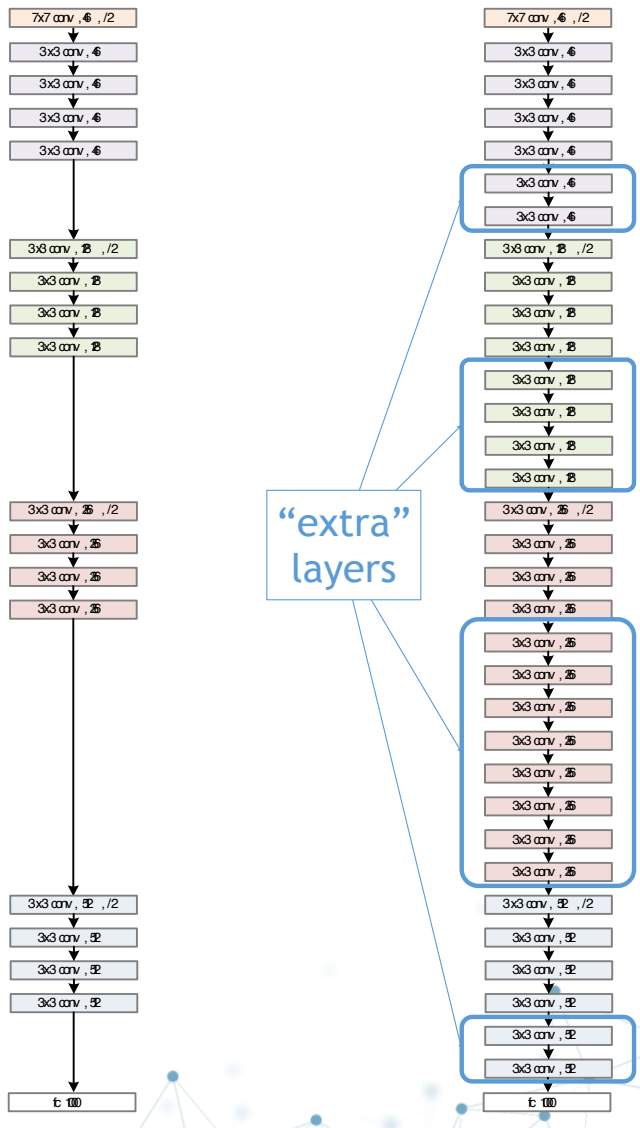
Stacking layers

- Deeper models should not have higher training error

- Solution by construction:
  - Train shallow model
  - Add additional layers set to identity
  - Train the deeper model further



* Figure credit: Kaiming He

Stacking layers

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  - Train shallow model
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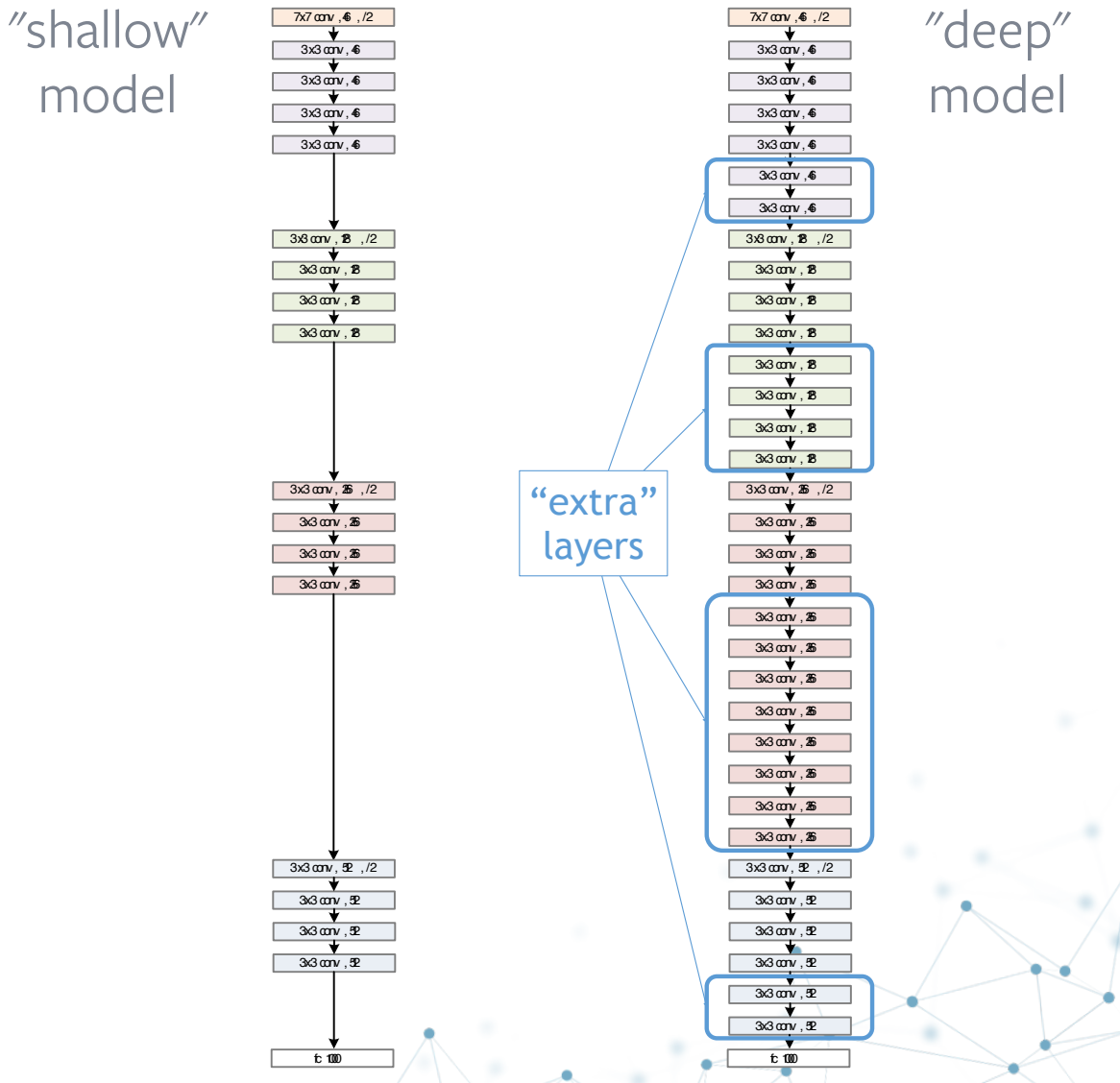
- Learning does not work well :(



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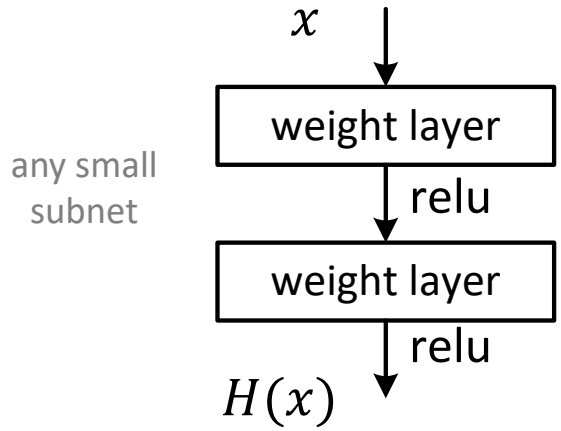
Residual connections

- Block architecture that achieves similar goal
- Take any "regular" network block...



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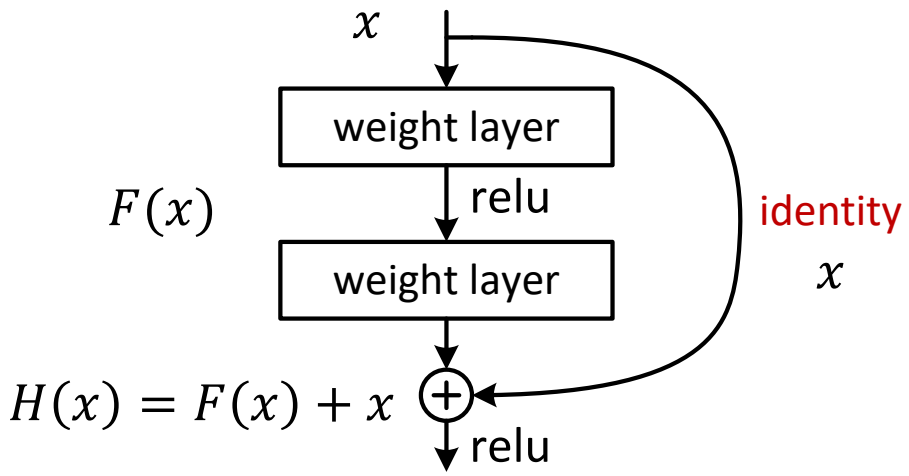
Residual connections

- Block architecture that achieves similar goal
- Take any "regular" network block... and make it **residual**:



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Residual connections

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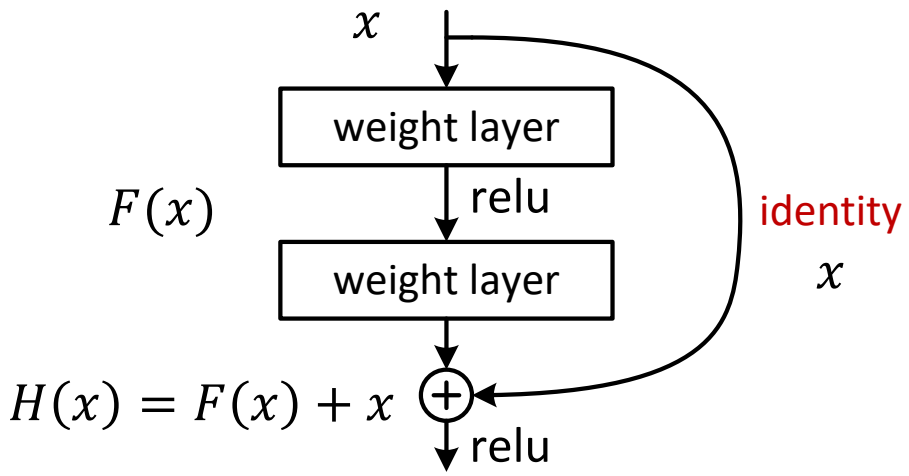
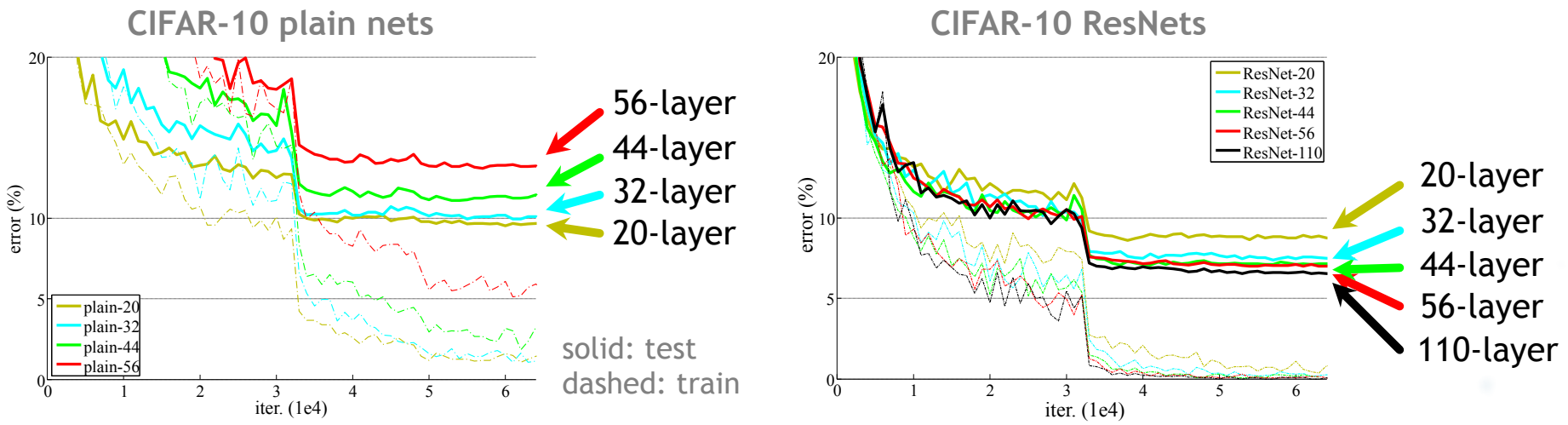


- Initializing weights to zero achieves the desired effect

* Figure credit: Kaiming He

Residual connections

- Deeper models can now be trained without problems:

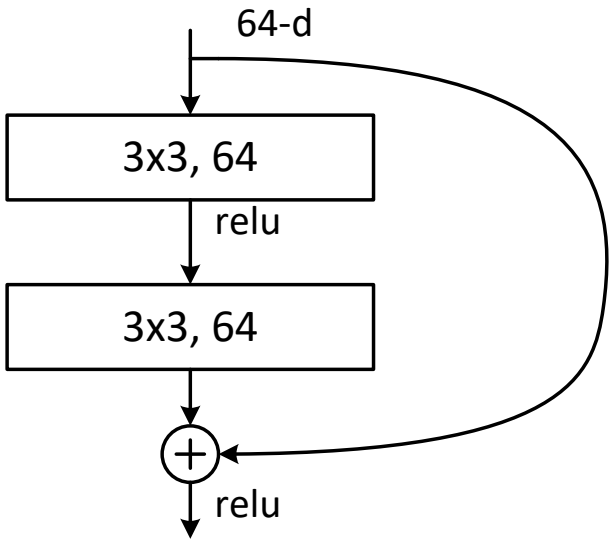


- Overfitting may still happen, but at least training error does not go up

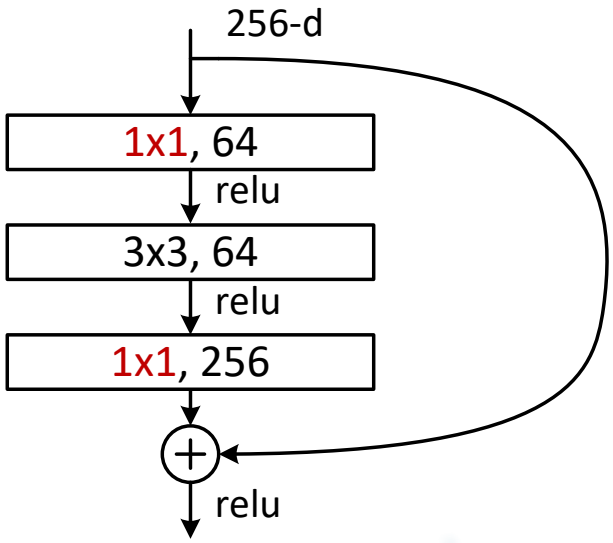
* Figure credit: Kaiming He

Residual networks

- In practice, residual networks (ResNet) use the following block design:



simple design

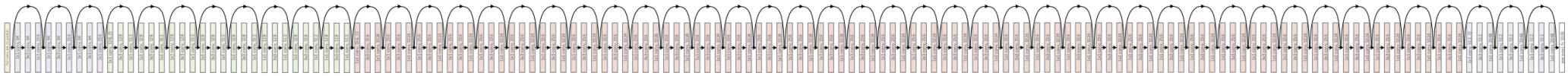


bottleneck design

* Figure credit: Kaiming He

Residual networks

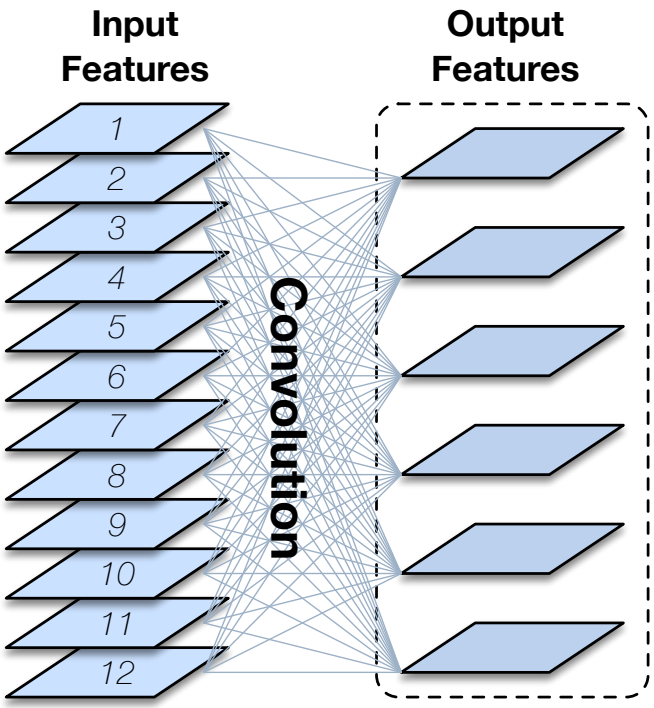
- Full model has pooling layers for downsampling
- All pooling layers do max-pooling but the last one does average-pooling



- Every time the image size halves, the number of channels is doubled

Group Convolutions

- In **group convolutions**, not all input channels feed into all output channels



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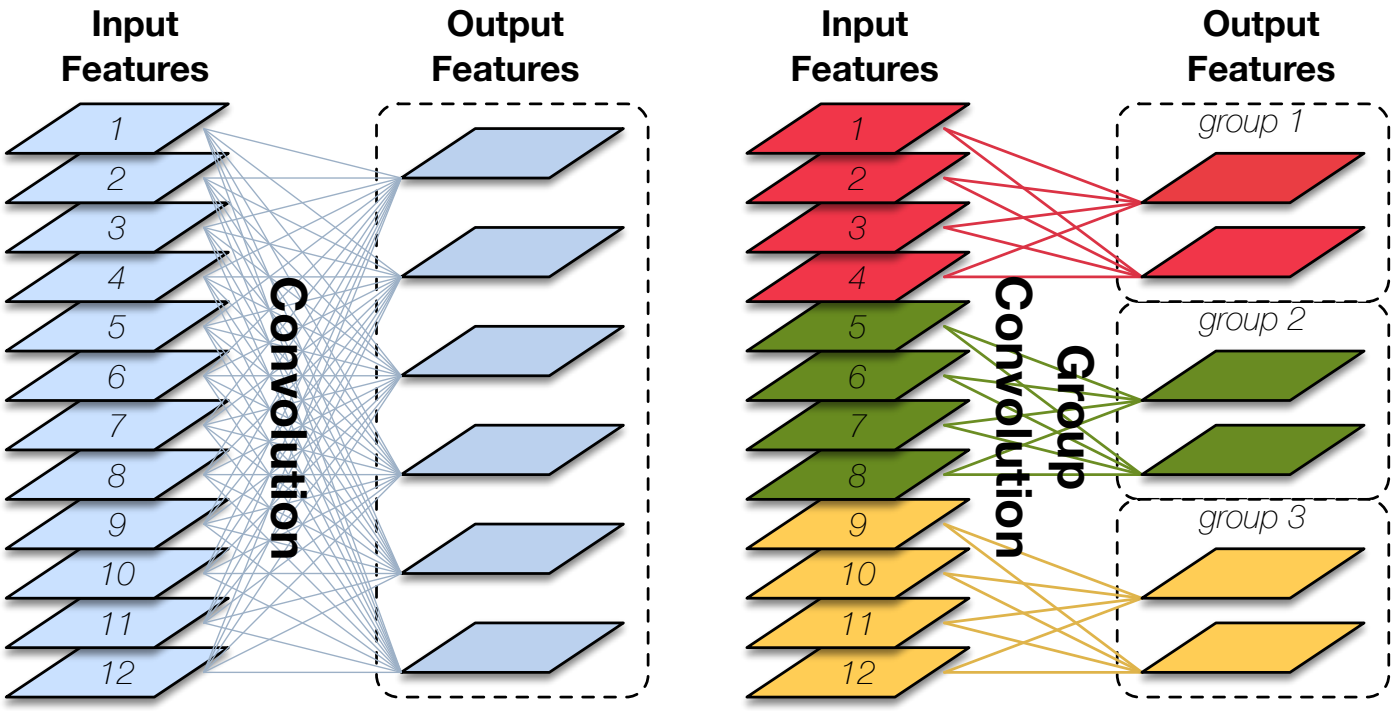
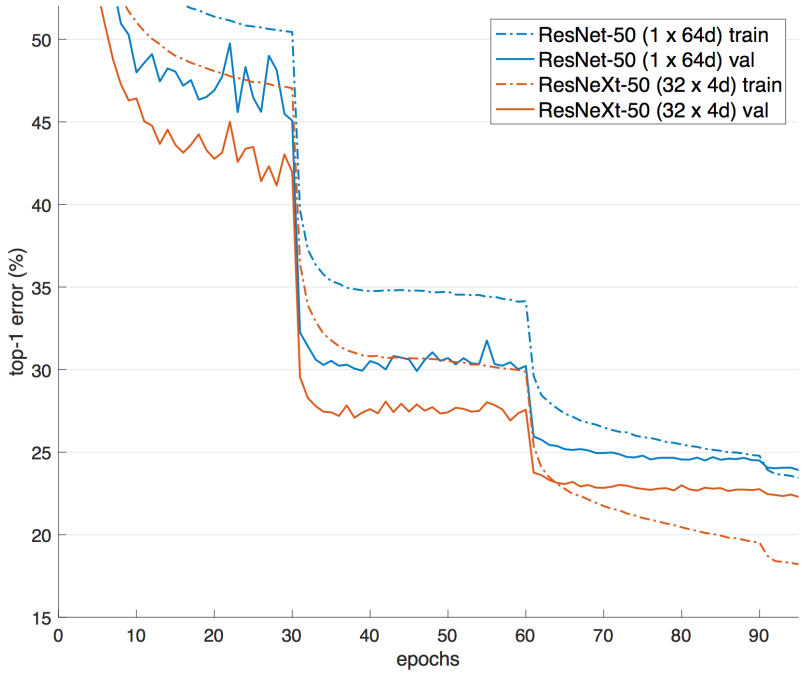


Group Convolutions

- **ResNeXt** is a popular model that uses group convolutions

- Group convolutions generally give a better **compute-accuracy trade-off**



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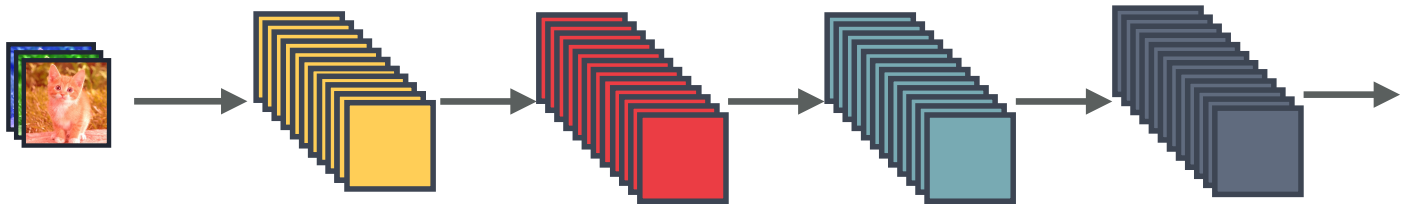
Standard connectivity

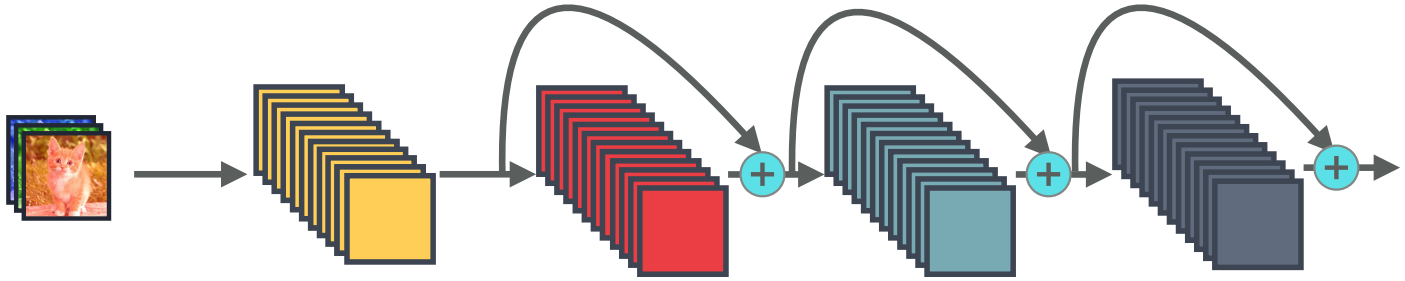


* Slide credits: Gao Huang

Residual connectivity: A new perspective

Funny properties of ResNets...

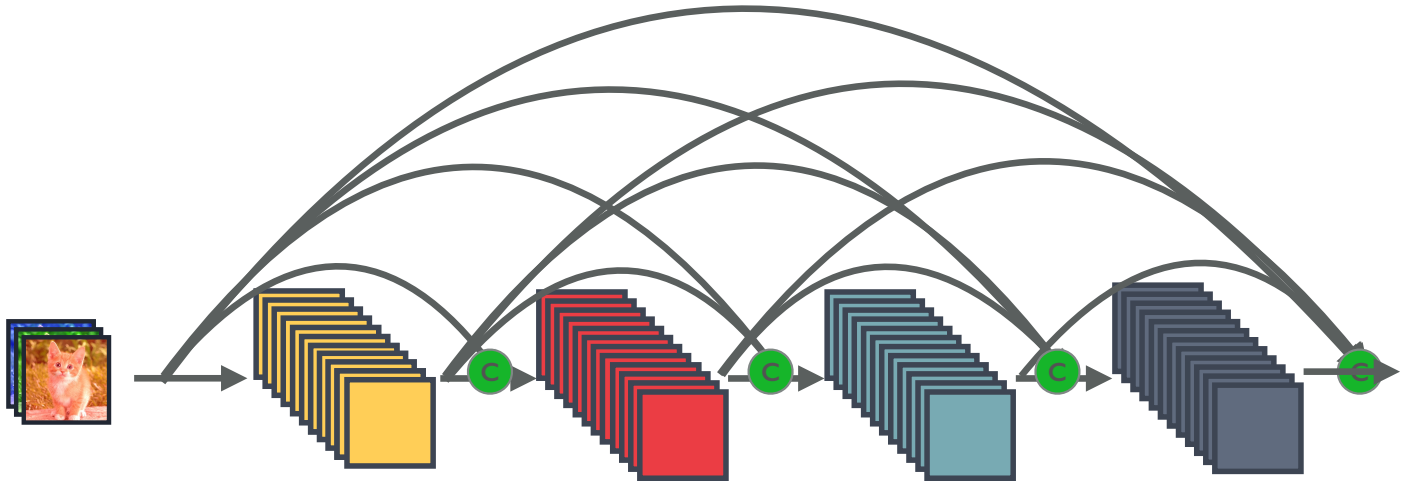
Identity, Interpretation, Propagation



⊕ : Element-wise addition

* Slide credits: Gao Huang

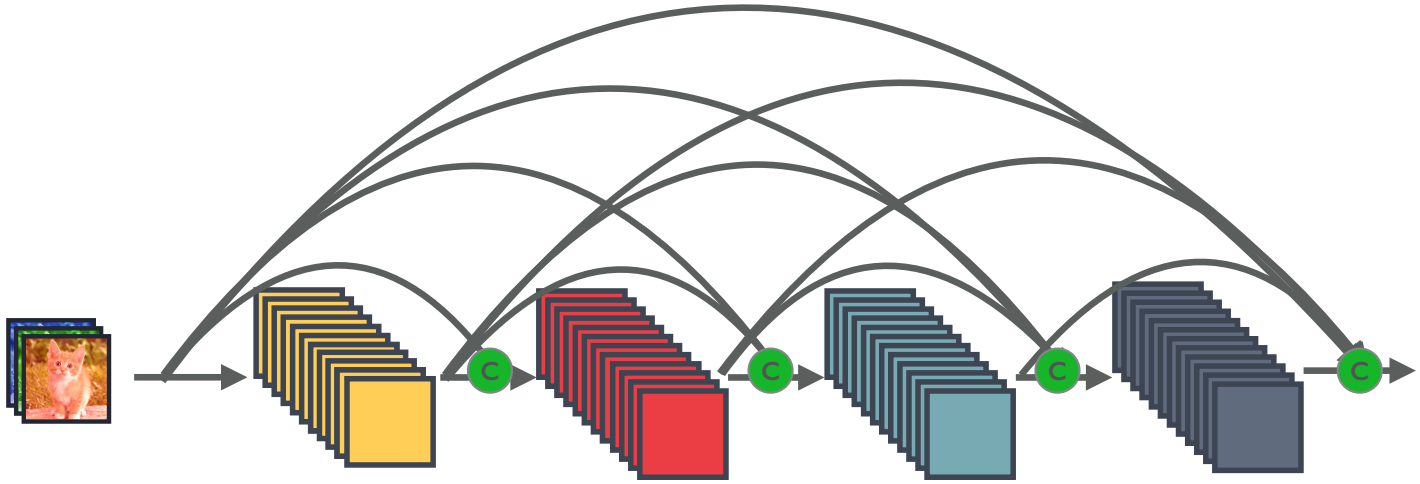
Dense connectivity: DenseNet



C : Channel-wise concatenation

* Slide credits: Gao Huang

Dense connectivity: DenseNet



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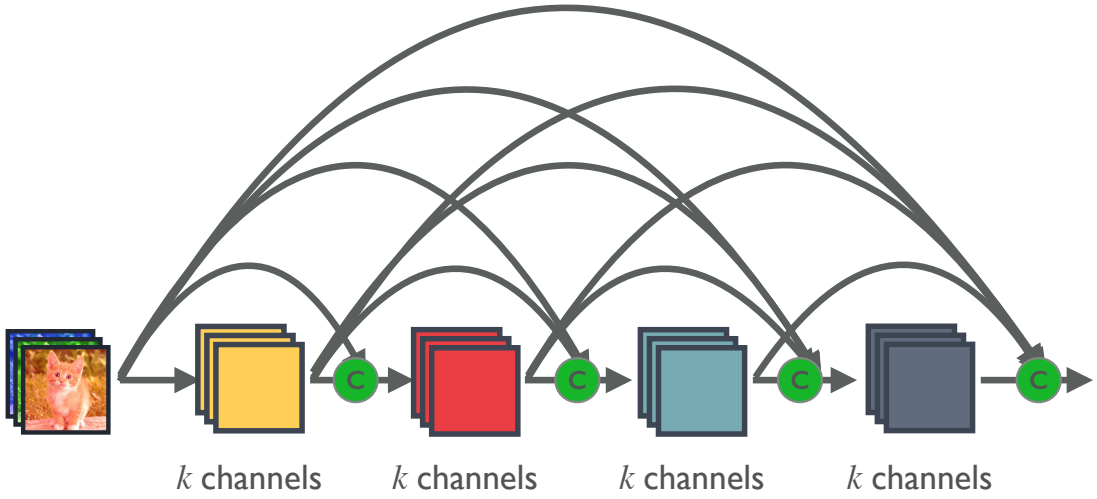
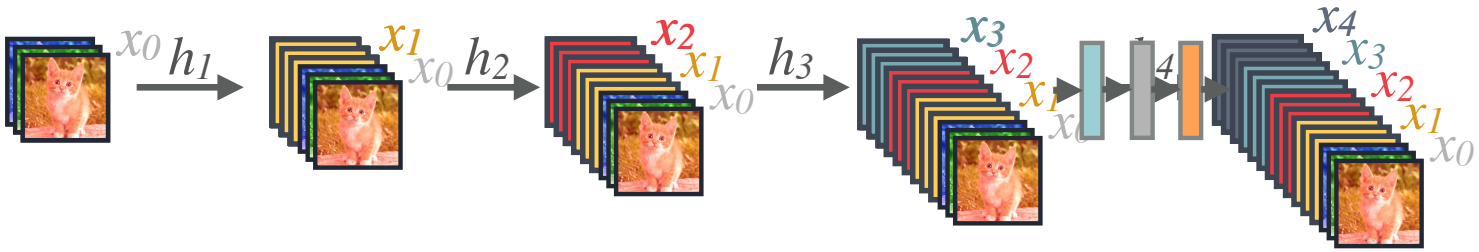
Dense connectivity: DenseNet



k : Growth Rate

* Slide credits: Gao Huang

Forward propagation



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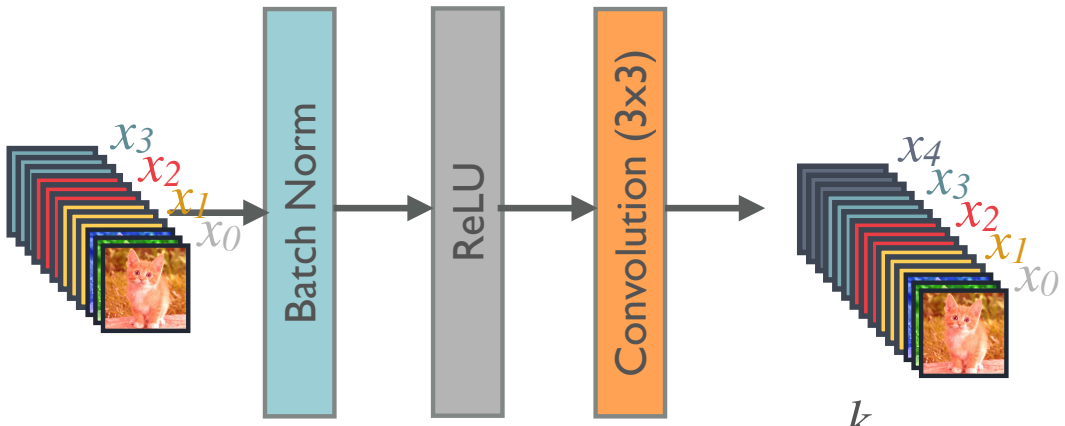
Composite layer in DenseNet

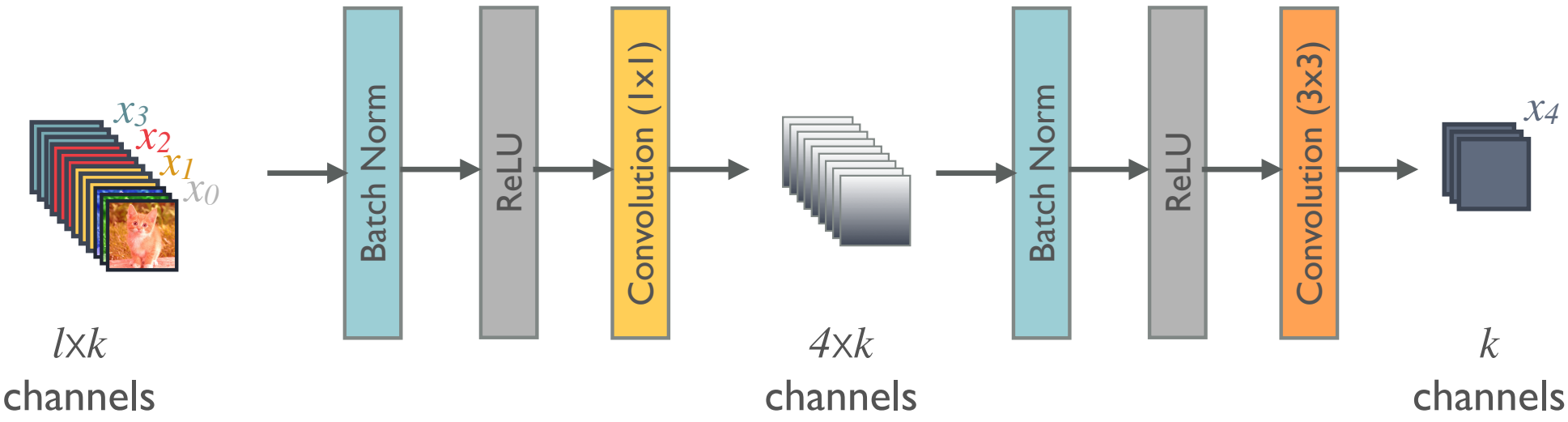


$$x_5 = h_5([x_0, \ldots, x_4])$$

* Slide credits: Gao Huang

Composite layer in DenseNet

With bottleneck layer:



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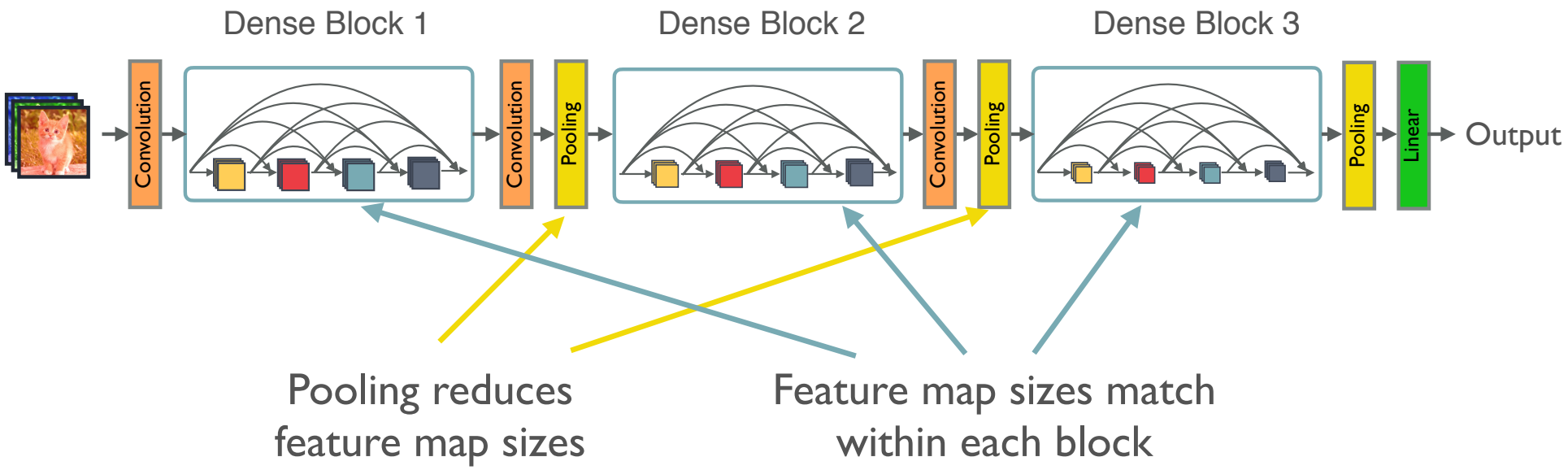
DenseNet



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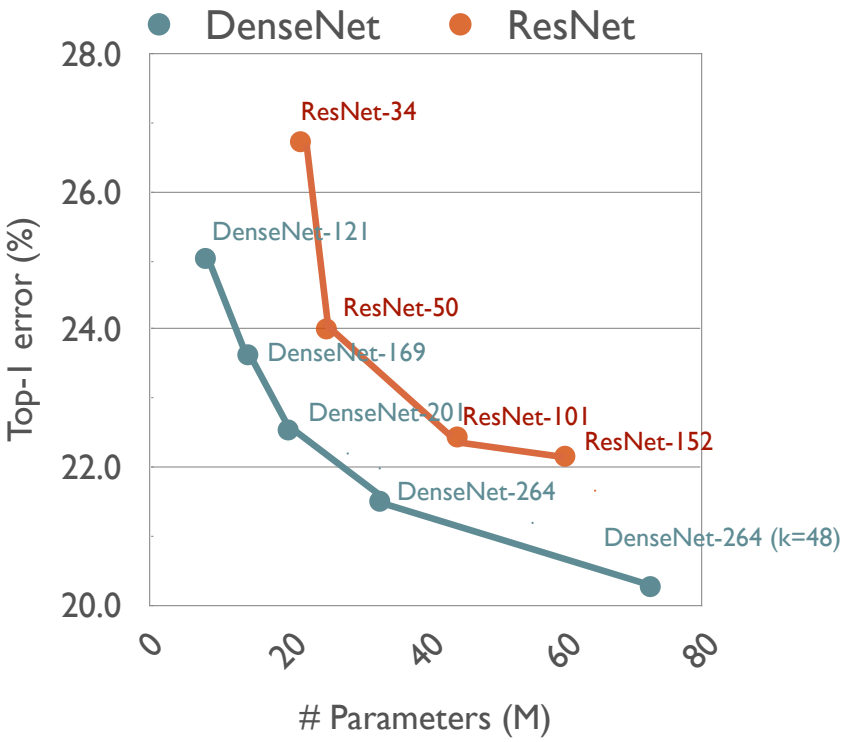
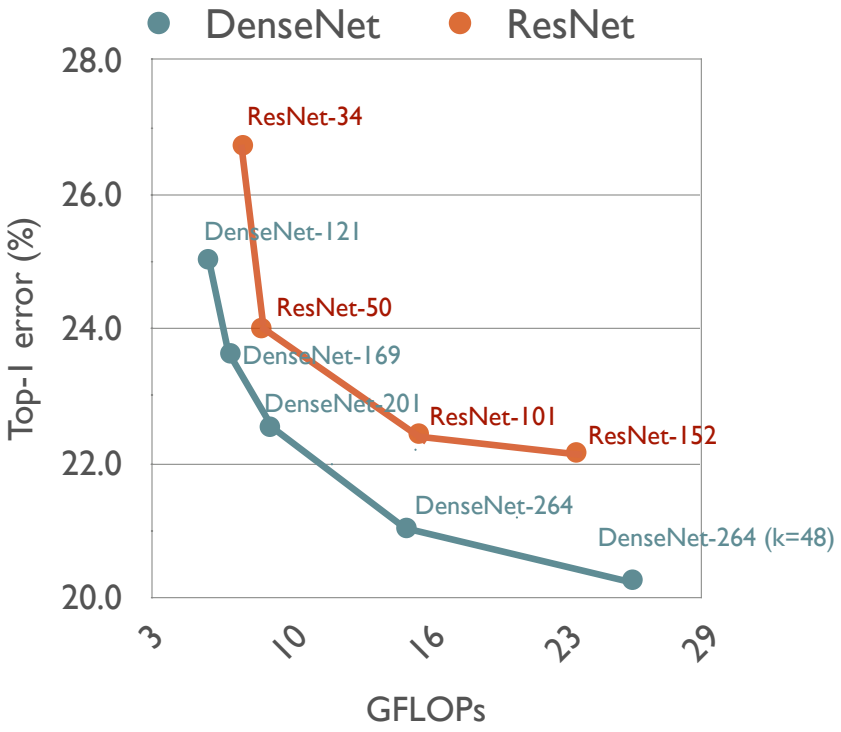
Results: ImageNet





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Model compression

- Can we train a small model to **mimic** a large model?

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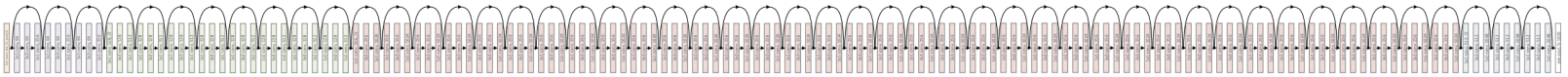
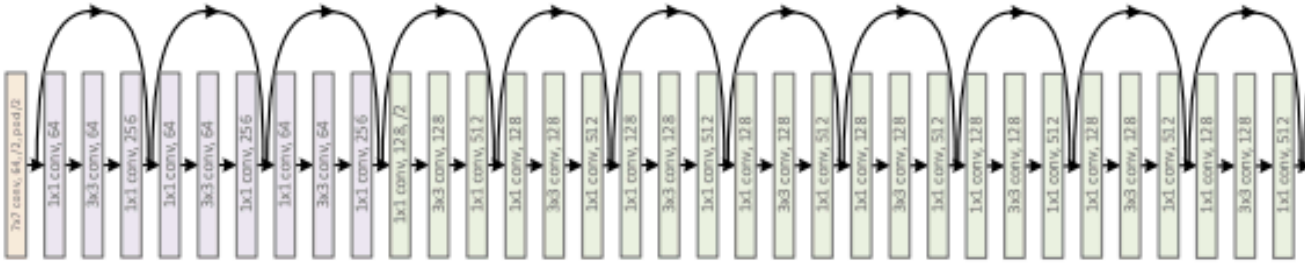
large "teacher" model





small "student" model

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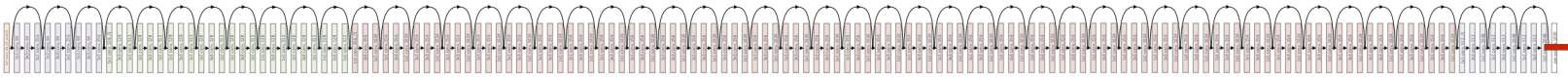
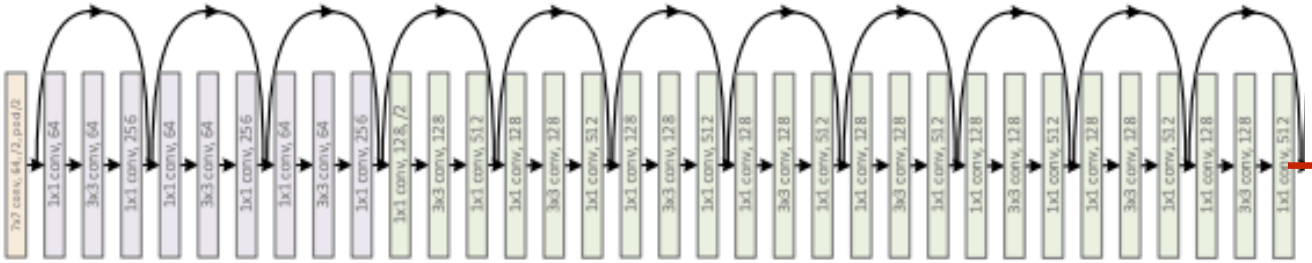


teacher output



student output

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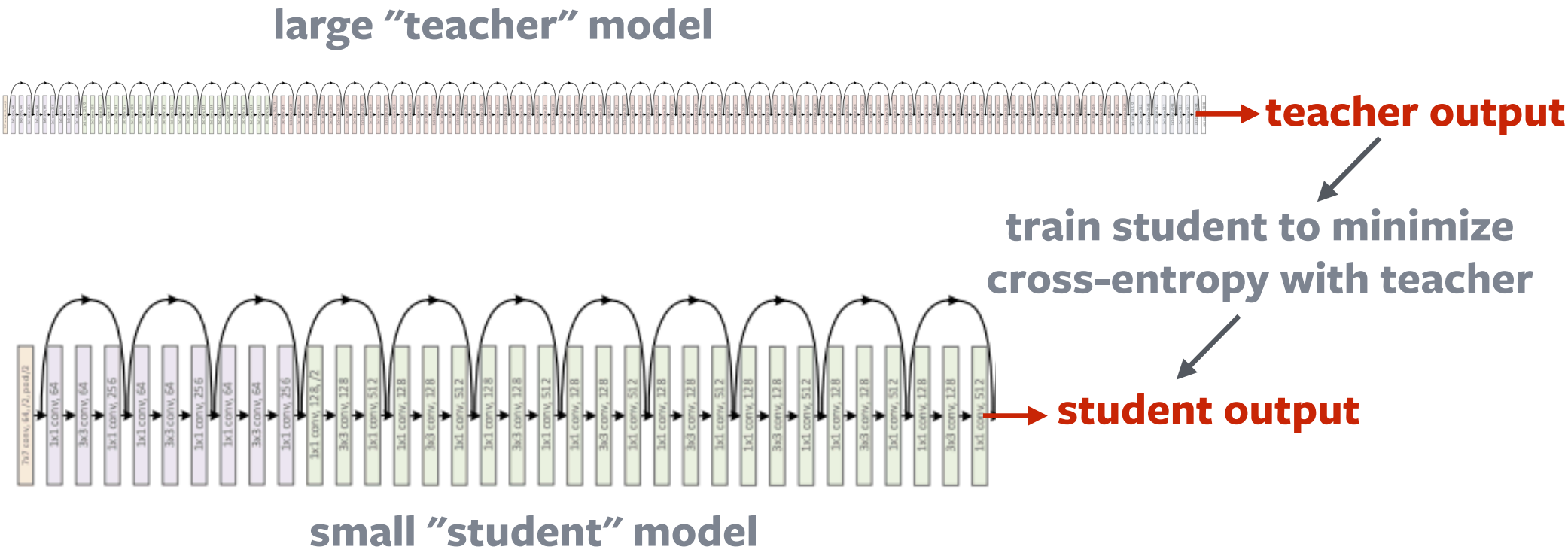

Model compression

- This actually works very well in practice:

System	Test Frame Accuracy	WER
Small model (normal training)	58.9%	10.9%
Big model	61.1%	10.7%
Small model ("distillation")	60.8%	10.7%

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- Why do you think this works?

Model compression

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- Why do you think this works?

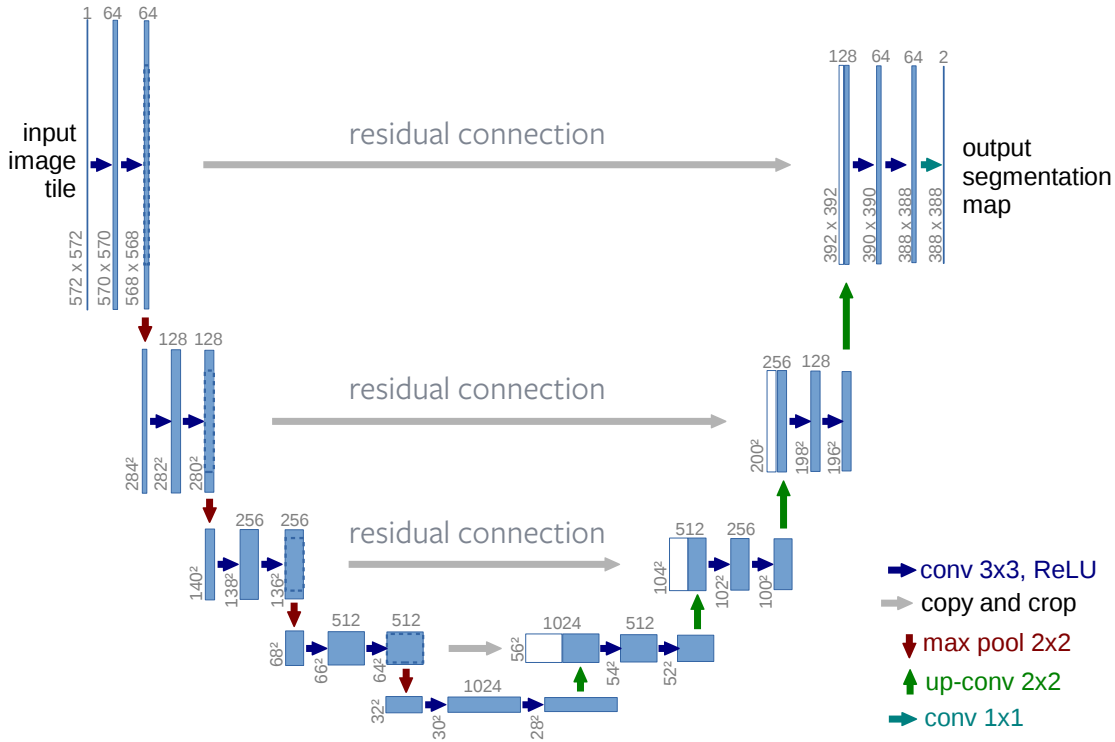
- **Soft targets!** Teacher tells student which examples to "ignore"...

Beyond image classification

- **Semantic segmentation**: Predict label for each pixel in the image

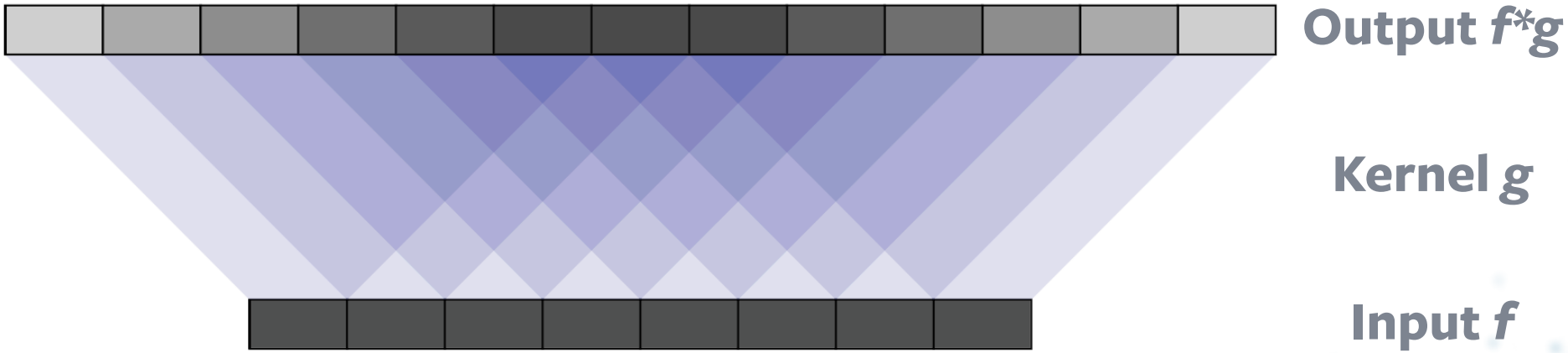
Beyond image classification

- **U-Nets** are an architecture designed for such problems:

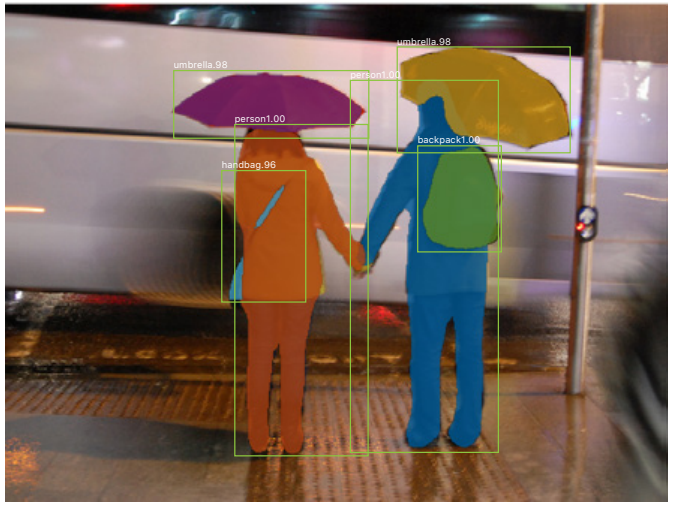


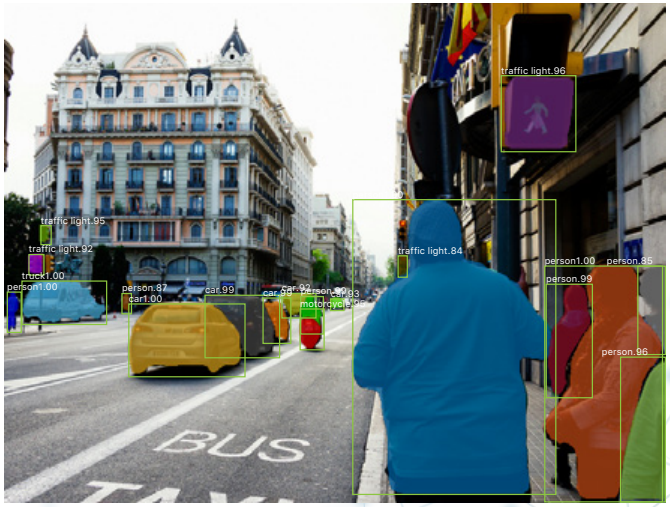
Beyond image classification

- Main additional ingredient in U-Nets is **deconvolution**:



* Credits: Chris Olah





* Results obtained with Mask R-CNN.

Summary

- Dense connectivity is an efficient alternative to residual connectivity
- Group convolutions reduce parameters and computation by reducing number of interactions between input and output channels
- Deconvolution allows for building segmentation networks

Reading material

- S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He. **Aggregated Residual Transformations for Deep Neural Networks**. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017

- G. Huang, Z. Liu, L.J.P. van der Maaten, and K.Q. Weinberger. **Densely Connected Convolutional Networks**. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.

- O. Ronneberger, P. Fischer, and T. Brox. **U-Net: Convolutional Networks for Biomedical Image Segmentation**. In *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2015.

Questions?